

**IN THE UNITED STATES DISTRICT COURT
FOR THE EASTERN DISTRICT OF PENNSYLVANIA**

**SECURITIES AND EXCHANGE
COMMISSION**

Plaintiff,

v.

BONAN HUANG, et al.

Defendants.

Case No. 2:15-cv-00269-MAK

**PLAINTIFF SECURITIES AND EXCHANGE COMMISSION'S
APPENDIX TO MOTION FOR SUMMARY JUDGMENT AGAINST
DEFENDANTS BONAN HUANG AND NAN HUANG**

**PART 2 OF 10
(0102-0145)**

A. Defendants Repeatedly Accessed the Credit Card Transaction Database over Three Years

20. I took two approaches to determining the extent of the Defendants' access to and use of Capital One's proprietary transaction database. First, I examined and summarized the contents of data files provided by Capital One that recorded incidents of access to Teradata through SQL queries. Second, I searched the Defendants' hard drives for SQL programs and output saved from those programs that capture data obtained by the Defendants from Teradata.

Database of SQL Queries

21. I understand that the Capital One database identified as "pcdw.t2_posted_trxn," a data table within Teradata, stores credit card transaction data. The database records, among other pieces of information, the date, the dollar amount, and the name of the merchant for purchases made by Capital One credit cardholders. Employees of Capital One access the transaction database by submitting queries written in a computer language called SQL.

22. I have reviewed 12 Microsoft Access data files from Capital One that contain listings of the SQL queries submitted by the Defendants over the period December 24, 2008 through January 8, 2015. The data files include an identifier of the computer from which the query was submitted, the date the query was submitted, and the text of the SQL query. The text of the SQL query typically includes instructions to access a particular database; draw certain elements of information from the database (such as transaction amount), according to a set of selection rules (such as, where merchant name= "walmart"), over a specified date range (e.g., from 01/01/2009 to present); perform manipulations on the

data (such as, calculate a sum); delete previous versions of the output; and create an output data set. As an illustration, Exhibit A shows two SQL queries from the Access databases, one from 2012 and one from 2014.

23. I combined the Access data files and searched the text of each SQL query to identify those queries that referenced the “pcdw.t2_posted_trxn” transaction database. I found that over the period February 1, 2012 through January 9, 2015, the Defendants completed 39,275 queries to the transaction database; that averages to over 1,091 per month. Bonan Huang submitted 11,335 completed queries (an average of 315 per month) and Nan Huang submitted 27,940 completed queries (an average of 776 per month).
24. One SQL program may extract transaction data for multiple companies, simply by expanding the list of merchant names in the selection rules. Indeed, in my review of the Defendants’ SQL programs, it was very common to see many company names specified in one program. For example, in the month of September, 2013 the Defendants submitted 99 programs that extracted transaction data for 50 or more companies at once. In subsequent months there were fewer such large programs submitted, but the number of companies per program increased, going from 149 companies in September, 2013 to 176 companies per large program in October, 2014.²

Programs and Outputs

25. I searched the Defendants’ hard drives for SQL programs and output files from those programs that captured Capital One transaction data. I found several types of output files,

² As used in this example, “company” is a stock ticker symbol. The Defendants’ SQL code allows for variants in the merchant name then maps those names to a ticker symbol (for example, merchant names “walmart”, “wal-mart”, and “sams club” map to “WMT”).

typically Microsoft Excel workbooks, in multiple locations on the hard drives, including output files sent as attachments to computer-generated e-mails to one of the Defendants.

26. I found several categories of output files that contain Capital One transaction information organized by company name or ticker symbol. For each category, I have reviewed computer code that was used to pull the Capital One data from Teradata.

27. In reviewing the files, I noted the company and ticker symbols associated with the downloaded transaction data.³ I combined the lists of ticker symbols that I found into one list. This is a list companies for which I found that the Defendants obtained transaction data from Capital One. I refer to this set of ticker symbols as the “tainted ticker list” and it appears in Exhibit B.⁴

28. **DONE Files:** On Nan Huang’s hard drive I found a folder labeled “personal.” Inside of this folder was a subfolder labeled “txn volume,” and within that folder was a subfolder titled “DONE.” This folder contains 172 Excel files. The names of the files correspond to company’s stock ticker symbols (e.g., jcp.xls, wmt.xls).

29. Each Excel file contains one or more tabs showing Capital One transaction data for the company summarized to the weekly or monthly level with the dollar amounts of transaction (in a column titled “txn_amt”) and counts of transaction (in a column titled “txn_cnt”).⁵

³ For example, I found a file in the DONE directory named “jcp.xls.” This file contained Capital One transaction data aggregated by month from 2009 to 2012, as well as J.C.Penney’s reported quarterly sales over the same period. I recorded this as ticker symbol, JCP.

⁴ I found additional output files and computer programs on the hard drives that access Teradata, pulling information on the same or a similar set of tickers.

⁵ Eighteen of the files are empty but for each one there is another file with the same ticker that does contain transaction data. Two files have filename that do not represent company ticker symbols (tmp.xls and txn_dt.xls) but they do contain transaction data.

30. For the majority of the DONE files, the transaction data begin in 2009 and for the rest the transaction data begin in 2010 or 2011. On average, the DONE files contain 46 months of historical Capital One transaction data.
31. Several of the DONE files also contain a tab that shows an SQL program that accesses Teradata and outputs the transaction data in a format consistent with the data seen in other tabs within the DONE file. An annotated example of an SQL program (found within the “wmt.xls” DONE file) can be seen in Exhibit C.
32. **RevEst Files:** Among Nan Huang’s files, I found five Excel files that begin with “RevEst” followed by a version number or other designation.⁶ These files contain rows of transaction data from Teradata, typically for the current quarter, sometime in 2014, and quarters from the previous year. All five RevEst files contain transaction data for 200 or more companies.
33. The data structure in the tab labeled “ratio_m” of these files corresponds to the data structure that is requested in the program SECP-COF-00019653, which pulls transaction data from Teradata.
34. The RevEst files also contain formulas and references to other tabs in the file that calculate year-over-year changes in transaction data. In addition, at least one of the files contains computer code that automates the process of accessing the internet and downloading company-specific information from “Yahoo Finance” and “Street Insider” on historic and upcoming earnings announcements, as well as equity analysts’ forecasts of revenue changes for upcoming earnings announcements.

⁶ Specifically, the five RevEst files I reviewed are these: REVEst((Autosaved-304182402364710960)).xls, REVEst.xls, REVEst_bkup2.xls, REVEst_tst1.xls, and REVEst_tst2.xls.

35. I found that all five RevEst files have another tab in the RevEst file (“run_time_hist”) that records the times at which the data were pulled from the Yahoo Finance and Street Insider websites. The run times range from March 8, 2014 to January 7, 2015.

36. **E-mail Files:** I found many additional computer programs and output files on Bonan Huang’s hard drive that contain company transaction data from Teradata. These are a set of attachments to e-mails sent to Bonan Huang in late 2014 and early 2015 containing transactions data, organized by ticker symbol and fiscal quarter. These e-mails were generated automatically by Bonan Huang’s batch file programs which collected and aggregated transaction data from Teradata.

B. Defendants Predicted Company Reported Sales Using Teradata Transaction Data

37. In my review of the programs and output files on the Defendants’ hard drives, I repeatedly found calculations and analyses that show the Defendants used transaction data from Teradata combined with publicly-available company quarterly reported sales to predict upcoming company quarterly sales.

38. I use the DONE file named “wmt.xls” to show the calculations performed by the Defendants with Teradata transaction data.⁷ Based on my review of the DONE files, the types of data and calculations found in “wmt.xls” are similar to those found in the other DONE files.

⁷ The file was created by Nan Huang, identified by user id oao009.

39. The file has several tabs, one of which (“script”) is a piece of SQL code. The SQL code is reproduced in Exhibit C. The program selects data from the table “pcdw.t2_posted_trxn” in Teradata, sums it by month, and labels the sum as “txn_amt.”
40. Another tab in “wmt.xls” is a tab titled “Overall” and it has a column of monthly data labeled “txn_amt.” The monthly data ranges from “2009-01” to “2013-08.” On the same tab, there are formulas that show the monthly transaction being summed to generate quarterly amounts. An annotated reproduction of the “Overall” tab from the Walmart DONE file is presented in Exhibit D.
41. The same tab shows Walmart’s historical actual reported quarterly sales figures pasted in and aligned with the quarterly transaction totals.⁸
42. The same tab contains several formulas that work together to create a forecast of Walmart’s sales for the fiscal quarter ending July, 2013.⁹ The calculation starts with the aggregation of the credit card transaction for May, June and July 2013, corresponding to Walmart’s second quarter for fiscal year 2014, 2014Q2.
43. Another component in the calculation is the percent of Walmart’s historical quarterly sales captured by Capital One credit card transaction in that quarter, which I refer to as the “capture rate.” The “Overall” tab shows this calculation for all the historic quarters and the capture rate ranges from 0.70% to 0.96%.
44. The forecast for Walmart’s 2014Q2 sales is equal to the transaction total for 2014Q2, scaled up by a composite capture rate.¹⁰ The composite capture rate is the capture rate

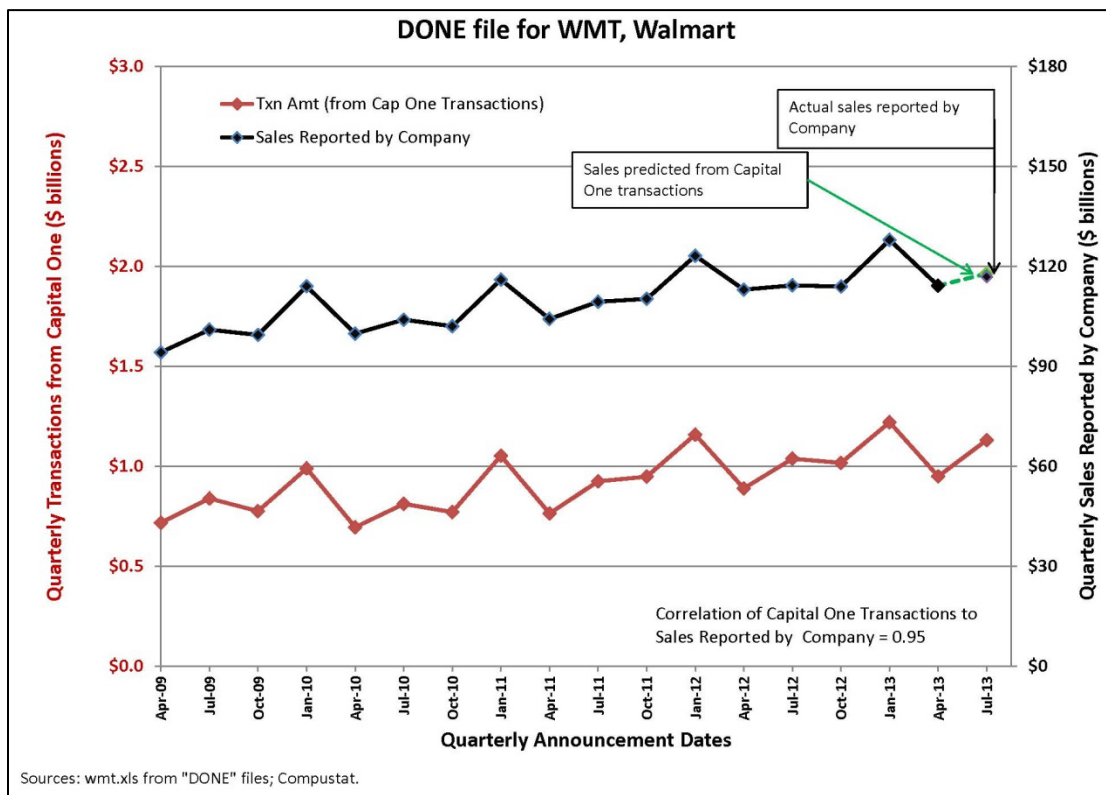
⁸ The column is not labeled, but I confirmed that the figures correspond (taking into account a decimal point movement) to Walmart’s historical reported quarterly sales as reported in Compustat.

⁹ Walmart’s fiscal year starts on February 1. The forecast formula appears in cell I56 of the “Overall” tab of “wmt.xls.”

¹⁰ The composite capture rate must be constructed because the capture rate for 2Q2014 is not yet available; it can only be calculated once Walmart reports its sales for 2Q2013.

calculated for the second quarter in the previous year (2013Q2) adjusted for any increase or decrease in the capture rate from 2013Q1 to 2014Q1.

45. To help demonstrate the Defendants' forecasting effort, I created the chart below that displays the data contained in the "Overall" tab. The red series shows the quarterly transaction amounts calculated from the records pulled from Teradata from April, 2009 to July, 2013; these values range between \$500,000 and \$1.5 million per quarter (as read along the left vertical axis). The black series shows Walmart's actual reported sales per quarter from April, 2009 to April, 2013; these values range between \$90 billion and \$140 billion per quarter (as read along the right vertical axis). The green dot at July, 2013 is the Defendants' forecasted Walmart sales for that quarter. The black dot is Walmart's actual reported sales for that quarter, which were reported on August 15, 2013, or 15 days after the close of the quarter.



47. Although the transaction data represents less than 1% of Walmart's total sales per quarter, the two lines are remarkably closely correlated. This co-movement can be quantified by a correlation coefficient, which in this case is 0.95.¹¹
48. As for the forecast of sales based on the Capital One data, the forecasted value for 2014Q2 is \$117.84 billion, which differs by only 1.4% from the actual value reported by Walmart.

VI. The Credit Card Transaction Information Obtained by Defendants was Valuable to Investors

49. I was asked to assess whether a reasonable investor would consider the transaction data that Defendants obtained from Teradata concerning company sales to be important when making a decision to buy or sell securities in those companies. To answer this question, I performed two analyses that demonstrate, in turn, that the credit card transaction data have the power to predict company quarterly sales revenue and to predict company quarterly revenue surprises (that is, instances when the company's reported revenues exceed or fall short of analysts' expectations). I find that transaction data obtained by the Defendants is predictive of each of these measures of company financial performance. This is true even though the Capital One transaction data for any particular company represents only a small fraction of that company's overall sales.^{12,13}

¹¹ A correlation coefficient is a measure of how closely two data series move together and can range in value from -1 (perfectly negatively correlated) to +1 (perfectly positively correlated). A correlation coefficient of 0 indicates that the two series are unrelated or independent.

¹² "Sample data can be used to describe a population. The population is the whole class of units that are of interest; the sample is the set of units chosen for detailed study. Inferences from the part to the whole are justified when the sample is representative." David H. Kaye and Freedman, David A., "Reference Guide on Statistics," in Reference Manual on Scientific Evidence (Washington, DC: Federal Judicial Center, 3rd ed., 2011), p. 217.

¹³ For the transaction data I use in the following analyses, the average coverage rate (percent of total quarterly company sales captured in Teradata) is 2.4%.

50. I use two technical terms to state my conclusions: “correlated” and “predictive.” The first conclusion that I draw is that the Capital One transaction data are correlated with company reported sales. My finding of “correlation” reflects the fact that, as illustrated in the Walmart chart above, the credit card transaction data moves together with company reported sales. I use a statistical test to test the hypothesis that the observed correlation is due to random chance. In addition, I have concluded that the Capital One data are predictive of company reported sales. Although correlation is often associated with predictive power, there are many examples of correlated data that are not predictive. I draw the stronger conclusion of the predictive value of the Capital One data based on my review of the Defendants’ predictive analyses. In addition, I observe that the Defendants had the ability to construct their estimates of company sales, say for the first quarter of the year, using Capital One transaction data from January 1 through March 31 well in advance of the company’s announcement of its sales for that quarter, which typically occur a month after the quarter end.¹⁴

51. In the analyses that follow, I use Capital One transaction data found on the Defendants’ hard drives and actual reported company sales and analysts’ sales forecasts from public data sources.

52. For the transaction data, I assembled a database of downloaded company transaction data from the DONE files and the RevEst files described earlier.¹⁵ I aggregated the transaction

¹⁴ Using the I/B/E/S data, I find the mean (median) number of days between the fiscal quarter end and the announcement date to be 30 days (29 days).

¹⁵ The thousands of SQL queries that were submitted by the Defendants to Teradata would have generated thousands of output files with transaction data from 2009 (or earlier) to 2015 for hundreds of companies. My analysis here is constrained to the transaction data I was able to locate in certain folders on the Defendants’ hard drives as they existed on the date the forensic images were made.

records to quarters aligned with the particular company's fiscal year.¹⁶ The resulting database has transaction data for 216 companies, with as few as one fiscal quarter of transaction data to as many as 23 fiscal quarters, with a median of 12 quarters per company. Except for the first two quarters where the data is more sparse, the transaction data is fairly equally spread over the 25 calendar quarters from 2008Q4 to 2014Q. The number of quarters of transactions depends on how many output files I found for each company and the date ranges covered by the output files.

53. I gathered information for each of the 216 companies' actual reported sales, announcement dates, and analysts' consensus estimates of revenues, over the same set of quarters using I/B/E/S.¹⁷ I combined the quarterly transaction database with the I/B/E/S database using company ticker symbol and fiscal quarter. The result is a dataset that has the dollar value of credit card transaction obtained by the Defendants from Teradata and the dollar value of sales revenue that the company subsequently reported for that same quarter, along with analysts' expectations of sales revenue for that quarter.

A. Sales Estimates Derived from Teradata are Predictive of Companies' Reported Sales

54. As I described in Section V, in my review of SQL programs and their output files from the Defendants' hard drives, I saw data and formulas in the DONE files that aggregated transaction data to quarters aligned with actual company reported sales. I also saw

¹⁶ In my review of the Defendants' DONE files and the RevEst programs, I saw that the Defendants tailored their aggregation of the transaction data. For example, for AAP, Advanced Auto Parts, both the DONE file and the RevEst code shows the Defendants aggregating transaction for 16 weeks for the first quarter of the fiscal year and for 12 weeks in each of the other three quarters to mimic AAP's reporting schedule.

¹⁷ Thomson Reuters I/B/E/S provides access to individual and consensus analyst forecasts and recommendations, as well as company actual performance data.

calculations that created forecasts of company quarterly reported sales. I created a chart depicting those data and calculations using the Walmart DONE file.

55. To illustrate the consistently predictive value of the Capital One transaction data, I created similar charts for 20 DONE files selected at random from the list of DONE files. The charts appear in Exhibit E.

56. The set of 20 charts demonstrates that the Walmart example was not unique with respect to the predictive quality of the Teradata transaction information. The other companies typically also show a high correlation between the transaction data and the company's actual reported sales.

57. I also conducted a similar analysis using transaction data from the larger number of companies for which I located transaction data in DONE files or RevEst files. For each company, I calculated the correlation coefficient between the quarterly transaction amount and the company quarterly reported quarterly sales. For each correlation coefficient, I conducted a statistical test at a 95% confidence level to measure the probability that an estimate of this magnitude would have occurred by chance if there truly were no relationship between the two series.

58. Each of the Defendants has claimed that the Capital One information was not material to investors because "purchases made using Capital One credit cards constituted a small percentage of all sales made at each of the Consumer Retail Corporations, and an even smaller percentage of total sales when taking into account other forms of payment."¹⁸ I have used a statistical analysis to evaluate their claim, formally testing the hypothesis that the Capital One data are unrelated to the company sales data.

¹⁸ Defendant Bonan Huang's Supplemental Answers to Plaintiff's Second Set of Interrogatories and Defendant Nan Huang's Supplemental Answers to Plaintiff's Second Set of Interrogatories

59. The chart in Exhibit F shows the correlation coefficients for the 132 companies for which I found a statistically significant correlation between the available Capital One transaction data from the DONE and RevEst files and company reported quarterly sales. I added a “Statistically Significant” indicator variable to the Tainted Ticker list in Exhibit B that is equal to one for these 132 companies.
60. Of the 215 companies for which I located transaction and sales data, 24 had only one or two quarters of transactions matched to a company sales revenue report, which is mathematically insufficient for calculating a correlation coefficient; for 59 companies, the correlation coefficient was statistically insignificant and for over 80% of these, there were only five or fewer quarters of data available.
61. For the set of 132 companies, 100 (76%) have correlations equal to 0.90 or stronger, 124 (94%) are 0.75 or stronger, and all are 0.50 or stronger.
62. I conclude that for 132 companies, the transaction data the Defendants obtained are highly correlated with company reported sales. In addition since the quarterly transaction data are available earlier than when the company publicly announces its quarterly sales, the transaction data are predictive of company reported quarterly sales. In my opinion, the results of this hypothesis test refute the Defendants’ claim. I find that, even though Capital One sales data are a small percentage of company reported sales, a reasonable investor would have considered this information to be important when making a decision to buy or sell securities in those companies.

**B. Sales Growth Estimates Derived from Teradata are
Predictive of Company Revenue Surprises**

63. In the previous analysis, I showed that the transactions data obtained from Teradata are predictive of company reported sales. Another source of information about future company sales comes from equity analysts. Equity analysts provide forecasts of company sales revenue, along with stock recommendations (buy, sell, hold), earnings forecasts, the analyst's identified "target prices" for the security over the next year, and the analyst's justification for his or her recommendation.
64. My second analysis tests the hypothesis that the transaction data obtained from Teradata provides additional ability to predict company reported sales growth, even after considering equity analysts' forecasts prior to the company's disclosure. That is, I test whether the transaction data would provide an investment advantage for an investor who already knows the analysts' forecasts, because the transaction data predicts revenue surprises.
65. I use the same database of Capital One transaction data found on the Defendants' hard drives, as described in the previous section. In this analysis, I include analysts' consensus revenue forecasts available in I/B/E/S, in addition to company reported sales. The analysts' consensus revenue forecast is the expected value of reported revenues for a particular company in a particular quarter. In my analysis, I use the consensus forecast most proximate and prior to the company revenue announcement date.
66. I test the predictive value of the Capital One transaction information using a generally accepted statistical technique called regression analysis.¹⁹ Regression analysis is widely used by economists to estimate the influence of one (independent) variable on another (dependent) variable while controlling for the influence of other (independent) variables.

¹⁹ Rubinfeld, Daniel, "Reference Guide on Multiple Regression," Reference Manual on Scientific Evidence, 3rd edition, 2011.

Economists have used regression analysis, for example, to identify the relative contributions of each element of the analyst report to the stock price reaction that occurs when the report is released.²⁰

67. I specify the variables in my regression as growth rates and in particular as year-over-year changes that measure quantities relative to the same quarter, one year earlier. This measure of growth adjusts for seasonality, which is a significant factor for most retailers.²¹ Changes can be positive, reflecting growth over time, or negative, reflecting contractions.

68. I calculate the year-over-year change for each company's quarterly reported sales revenue as the dependent variable. The "independent" variables are 1) the analysts' consensus forecast of the company quarterly sales revenue divided by the one-year-ago company reported sale revenue, and 2) the year-over-year change in quarterly transactions.²²

69. The data set for my regression analyses contains 1,714 observations where all three year-over-year change variables are available for the company fiscal quarter; there are 201 companies and an average of 8.5 quarterly sales revenue announcements per company over the period December, 2009 to November, 2014. I conduct two pair of regressions, one pair includes all 201 companies represented in the data set, and one pair includes only the observations for companies for which I found a statistically significant

²⁰ Asquith, Paul, M. Mikhail, and A. Au, "Information Content of Equity Analyst Reports," *Journal of Financial Economics*, Volume 75, Issue 2, February 2005, Pages 245–282.

²¹ This is the same calculation that I observed being performed by the Defendants in the DONE output files, the RevEst files and others located on the Defendants' hard drives.

²² If the previous year's quarterly value is not available, then the data record for the quarter falls out of the analysis.

correlation between transaction data and company reported sales revenues (131 companies with an average of 11.3 quarterly sales revenue announcements).

70. The regression equation to be estimated is this:

$$\Delta \text{Sales Revenue} = \alpha + \beta * \text{Analyst Expectations} + \delta * \Delta \text{Capital One Transactions}$$

where Δ indicates year-over-year change, Analyst Expectations are divided by the prior year's reported sales revenue, and α , β , and δ are coefficients to be estimated.

71. If analysts' forecasts are accurate, then the Analyst Expectations variable will be strongly and positively correlated with the change in Sales Revenue (that is, that β will be positive and be statistically significant). If the change in Transactions conveys no information beyond the Analyst Consensus, then I expect the δ coefficient to be statistically insignificant; on the other hand, if the change in Transactions does provide additional information for the change in reported sales, the δ coefficient will be statistically significant.

72. The regression results are shown in the table below for two sets of companies and for two types of announcement events. The first column in each pair of results shows the

Forecasting Reported Quarterly Sales Growth for Tainted Companies				
Dependent Variable: Reported Sales _{q,t} / Reported Sales _{q,t-1}				
	All Companies		Companies with Statistically Significant Correlation of Transactions to Sales	
	All Announcements	Traded Announcements	All Announcements	Traded Announcements
Intercept	-0.118 (-10.58)	-0.128 (-7.05)	-0.123 (-9.54)	-0.132 (-6.44)
Analyst Expectations	1.052 (94.62)	1.053 (49.34)	1.047 (70.01)	1.044 (36.16)
Growth in Capital One Transactions	0.059 (6.98)	0.064 (3.06)	0.068 (5.84)	0.075 (2.93)
Number of observations	1,714	380	1,481	325
Adjusted R-squared	0.94	0.96	0.93	0.95
Note: Each observation is a company-quarter, where the quarterly value is measured relative to the value in the same quarter of the previous year. Growth in Capital One Transactions is measured as Transactions _{q,t} / Transactions _{q,t-1} . Analyst Expectations _{q,t} are measured relative to Reported Sales _{q,t-1} . T-statistics are in parentheses and are based on heteroskedasticity-robust (or White) standard errors.				

estimated relationship when all available earnings announcements are included. The second column in each set restricts the set of announcements to those over which the Defendants traded.²³

73. The results across all four specifications are very similar. In the specification with all companies and all announcement dates, I find that the Analyst Expectation variable has a large positive coefficient and is highly statistically significant.²⁴ Notably, the growth in Transactions also has a positive, highly statistically significant relationship with growth in company Sales Revenue. This means that the growth in transaction give the holder of the information an advantage over the analysts' consensus.

74. In the regression focusing only on announcements the Defendants traded over, the coefficient on the growth in analysts' forecasts is about the same magnitude and is statistically significant, as it was in the regression including all announcements. Despite the dramatic decrease in the number of observations contributing to the regression, the coefficient on the growth in transactions increases in magnitude and remains statistically significant, meaning that the transaction information helps to predict company revenue surprises, particularly for events the Defendants traded over.

75. In the second set of columns, I restrict the regressions to those companies for which I found a statistically significant correlation between the company transaction data and reported sales. The Analyst Forecast coefficient is largely unchanged and the

²³ That is, the announcements where one of the Defendants opened a position in the company's stock prior to a revenue announcement and closed the position after the company's announcement. To identify this set of announcements, I relied on a file provided by counsel from Dr. Matthew Cain.

²⁴ A t-statistic of 1.96 or larger indicates statistical significance at the 95% confidence level or better.

Transactions coefficient is slightly larger and still statistically significant, despite the reduction in sample size.

76. Both of the Defendants claim that “substantially similar credit card data is made available publically by credit card companies to analysts and others.”²⁵ The results of my statistical tests refute this claim. In fact, these results show that the information about company sales growth contained in the transaction data was not publicly known. If the Capital One transaction data had been publicly available, the Analyst Expectations variable would have reflected this information and the Transaction coefficient would be zero.
77. These results taken together indicate that when the growth in credit card transactions is positive (negative), it is more likely that the company sales revenues will exceed (fall short of) analysts’ expectations (in either case, resulting in a “revenue surprise”). The credit card information would have been important for investors because, when a company beats analysts’ expectations, its stock price generally rises, giving an opportunity for an investor with foreknowledge of this event to make profits by “going long” in that company’s stock. The same is true when a company falls short of analysts’ expectations; an investor with foreknowledge of this can make profits by taking a short position that company’s stock.
78. My conclusion that investors would have valued the Capital One transaction information is also supported by widely held views by economists regarding the importance of company sales information. Each Defendant has claimed that the Capital One data “did not provide any insight on a host of factors that impacted the stock price for each Consumer Retail Corporation, such as general market conditions, industry-specific issues,

²⁵ Defendant Bonan Huang’s Supplemental Answers to Plaintiff’s Second Set of Interrogatories and Defendant Nan Huang’s Supplemental Answers to Plaintiff’s Second Set of Interrogatories

or company-specific factors beyond the amount of sales made with Capital One credit cards.”²⁶ However, there is widespread agreement among economists and finance practitioners that information about a company’s future reported sales figures is useful and important for investors. After all, sales revenues are the starting point for profits and cash flows. Consequently, many investors are aware that “sales growth ... is the fundamental driver of firm growth.”²⁷

79. Financial practitioners, including CFOs and analysts, share the perspective that firm sales revenues are an important metric for investors. For instance, a survey of 401 financial executives asked the question, “Rank the three most important performance measures reported to outsiders.” After earnings, the financial executives identified revenues as the second most important firm performance measure.²⁸ A similar sentiment is expressed by economists in a recent published study, who opined, “Next to earnings, revenues forecasts are perhaps the most widely followed performance metric by analysts.”²⁹
80. Based on the results of my regression analyses, it is my opinion that a reasonable investor would consider the company credit card transaction data that the Defendants obtained from Capital One important when making his or her decision to buy or sell the securities of those companies.

VII. Defendants’ Trading Profits Were Extraordinary

²⁶ Defendant Bonan Huang’s Supplemental Answers to Plaintiff’s Second Set of Interrogatories and Defendant Nan Huang’s Supplemental Answers to Plaintiff’s Second Set of Interrogatories.

²⁷ Fairfield, P., S. Ramnath, T. Lombardi Yohn, “Do Industry-Level Analyses Improve Forecasts of Financial Performance?” *Journal of Accounting Research*, Vol. 47 No. 1 (March 2009), p. 149.

²⁸ Graham, J., C. Harvey and S. Rajgopal, “The Economic Implications of Corporate Financial Reporting,” *Journal of Accounting and Economics*, Vol 40, December 2005, Pages 3–73.

²⁹ Rees, L., and K. Sivaramakrishnan, “The Effect of Meeting or Beating Revenue Forecasts on the Association between Quarterly Returns and Earnings Forecast Errors,” *Contemporary Accounting Research*, Vol. 24 No. 1 (Spring 2007), p. 259.

81. I analyzed each Defendant's trading activity and monthly statements from their brokerage accounts between January, 2012 and December, 2014. For purposes of measuring quarterly, annual, and total portfolio returns from January, 2012 through December, 2014 by individual, I combined the activity of six of Nan Huang's accounts, and I also separately combined the activity of seven of Bonan Huang's accounts.^{30,31,32}
82. I used two common methods to calculate the Defendants' rates of return on their investments: a "cash-in/cash-out" calculation and the "Modified Dietz" method.³³
83. The cash-in/cash-out rate of return is a ratio. The numerator is the investor's net gain, which is his ending balance less his initial investment plus the net withdrawals he made during the period. The denominator is the initial investment amount. All this information is available from the investors' monthly brokerage statements. The rate of return calculated this way will be a return over the entire period, three years in this case; it easily can be expressed as an annual rate to make it more readily comparable to returns on other investments.

³⁰ For Nan Huang my analysis focused on the following trading accounts: OptionsHouse (SPD-45586, SPD-64034, SPD-64046), Interactive Brokers (U1330854), COR Clearing /Just2Trade (68265967), E*Trade (67956338). I excluded the following accounts due to lack of monthly statements: Zecco Trading (4ZW83710), MB Trading (2FC-12888) and COR Clearing /Just2Trade (68265967), after March 31, 2013. These excluded accounts represent on average, 0.4% of holdings.

³¹ For Bonan Huang, my analysis focuses on these accounts: OptionsHouse (SPD-69674, SPD-91874, 4ZE-89435), Scottrade (68386941), TradeStation (17402409, 17410233), and E*Trade (68427490). Statements for Scottrade from October 2012 through March 2013 are not available. Zero balances were assumed for those months based on September 2012 closing balance and April 2013 opening balance.

³² E*Trade accounts for Nan Huang and for Bonan Huang are adjusted to treat shares of Capital One (COF) received under employee stock purchase plan as positive cash flows based on the COF stock price on day of receipt. I obtained data on COF stock prices from the Center for Research in Securities Prices (CRSP) database.

³³ The Modified Dietz method is a commonly used by the SEC and by investment professionals to calculate deposit- and withdrawal-adjusted returns. See, for instance, The CFA Institute, *Global Investment Performance Standards Handbook*: 3rd edition, 2012.

84. The Modified Dietz rate of return is similar to the cash-in/cash-out method but is more complicated to calculate because it takes into account the lengths of time between the initial investment, the withdrawals, and the ending balance.
85. Bonan Huang started 2012 with an initial balance of \$11,343. By the end of the December, 2014, he had a balance of \$1,032,496, more than 91 times his initial balance. During this time, he had net withdrawals of \$680,196. In other words, Bonan Huang generated \$1,712,692 (the sum of his ending balance and his withdrawals) from his initial investment. Using the cash-in/cash-out method, I find that Bonan Huang earned a 14,999% rate of return over the three years, which equates to an annualized return of 432%. Using the Modified Dietz method, Bonan Huang earned a 94,563% return over three years, which equates to an annualized return of 882%.
86. Nan Huang's trading activity turned an initial investment of \$11,459 in 2012 into \$1,492,970 (his ending balance of \$268,677 plus net withdrawals of \$1,224,293) at the end of 2014. The cash-in/cash-out method yields a return over three years of 12,929%, which equates to an annualized return of 407% for each year. Using the Modified Dietz method I find Nan Huang's rate of return was 29,673%, or 568% per year.
87. To give perspective to Defendants' performance, I compare their returns to the returns earned by a broad market index, in the consumer discretionary sector, and in the hedge fund industry.³⁴ Exhibit G shows the yearly and three-year returns for these three sources. I analyze the consumer discretionary sector—which includes Amazon and Starbucks—because it is the core market segment of most of the companies whose securities the Defendants traded.

³⁴ A hedge fund pools money from a set of investors. The hedge fund manager selects investments for the fund according to a particular strategy. The investors share the funds gains or losses.

88. The performance of the Defendants' portfolios of investments between January, 2012 and December, 2014 were extraordinary when compared to that of the broad equity market and the more specific consumer discretionary sector. The S&P 500 index, which represents the broad market, returned a three-year return of 64%, while the sector index returned 93%.
89. Bonan Huang's three-year cash-in/cash-out returns were 235 times greater than the S&P 500 index and 161 times greater than the sector index. Nan Huang's three-year cash-in/cash-out returns were 203 times greater than the S&P 500 index and 139 times greater than the sector index.
90. As another comparison, I capture the performance of the hedge fund market by analyzing the returns of 1,049 hedge funds. These hedge funds are the top performing hedge funds for each fund manager and strategy combination that reported monthly returns to the Lipper TASS database from 2012 through 2014. The chart in Exhibit H shows the range of three-year returns earned by these hedge funds.
91. Between January, 2012 and December, 2014, the median hedge fund achieved a three-year return of 24.3%. This is far below the 14,999% return earned by Bonan Huang and the 12,929% return earned by Nan Huang during this same time period. The Defendants' returns far exceeded even the top performing hedge funds' three-year returns. The hedge fund at the 95th percentile earned 96.9%, while the top performing fund reported a 1,552% return.
92. I considered the question, what portion of each Defendant's trading profits is attributable to trades in "tainted stocks" for which the Defendants obtained transaction data from Capital One. To analyze this issue, I was provided with a database of the Defendants'

trading activity produced by Dr. Matthew Cain. I used this data to calculate the Defendants' net profits from trades in tainted tickers versus their net profits from other securities. My calculations, shown below, demonstrate that the vast majority of each Defendant's trading profits are due to their trades in tainted securities.

Portion of Defendants' Net Trading Profits from Tainted Securities		
	Bonan Huang	Nan Huang
Non-Tainted Securities	-\$2,918	\$196,902
Tainted Securities	\$1,764,049	\$1,313,767
Total trading profits	\$1,761,131	\$1,510,669
% Profits from Tainted Securities	100%	87%
Source: "Net Profits by Defendant" produced by Dr. Matthew Cain. Counting only the set of securities with statistically significant correlation between Capital One transaction data and reported company sales as the tainted securities, the percent of profits from tainted securities is 86% for Bonan Huang and 100% for Nan Huang.		

93. I conclude that Nan Huang and Bonan Huang each earned extraordinary rates of return, whether measured using the cash-in / cash-out or the Modified Dietz Method, from their trades in the tainted securities when compared to even the most successful investors among a set of sophisticated professional investors.

Signature



Stephen Graham

September 18, 2015

Appendix 1: CV of Stephen Graham

STEPHEN GRAHAM

Financial Economist
Office of Litigation Economics
Division of Economic and Risk Analysis
U.S. Securities and Exchange Commission
Burnett Plaza, 801 Cherry Street
Suite 1900, Unit 18
Fort Worth, TX 76102
(817) 978-6455, grahamst@sec.gov

Stephen Graham is a Financial Economist in the Office of Litigation Economics at the U.S. Securities and Exchange Commission in the Fort Worth Regional Office. He analyzes securities and financial market data using economic theory and statistical methods to provide economic and statistical analyses on matters of interest to the Commission. These analyses include analyzing trading patterns, market manipulations, and asset management practices; quantifying harm to investors; and estimating ill-gotten gains.

Prior to joining the S.E.C., Mr. Graham spent fifteen years in private-sector economic consulting firms where he conducted economic and market analysis, large scale data analysis, business forecasting, and damage calculations. He has also worked on the design, implementation and maintenance of computer and network systems.

EDUCATION

PhD studies in Economics (Incomplete), Texas A&M University, TX, 2000
B.A. (Economics, History minor), Central State University, OK, 1991

PROFESSIONAL EMPLOYMENT

U.S. SECURITIES AND EXCHANGE COMMISSION, Fort Worth, TX
Division of Economic and Risk Analysis, Office of Litigation Economics
Financial Economist, July 2012 – Present

ADVANCED ANALYTICAL CONSULTING GROUP
Senior Manager, June 2010 – July 2012

DELOITTE FINANCIAL ADVISORY SERVICES LLP, Dallas, TX
Manager, Economic and Statistical Consulting, Sept 2002 – June 2010

ANDERSEN LLP, Chicago, IL
Manager, Economic Consulting, Nov 2001 – Sept 2002

WELCH CONSULTING, College Station, TX
Economist, Aug 1997 – Oct 2001

PROGRAMMING EXPERIENCE

Mr. Graham has 17 years of experience programming in various software packages, primarily SAS and STATA for statistical analysis, and various versions of SQL, Microsoft Access, Microsoft Excel, and Python for manipulation and analysis of databases. He has designed the architecture for entire graphical user interface (GUI) systems using Javascript, PHP and custom libraries used in the front end to Postgres which was used as the storage layer. He has developed maximization routines in kNitro. Mr. Graham has completed courses at Coursera in Machine Learning which were performed entirely in Octave. He has written computer maintenance, billing and administrative programs in Perl, Visual Basic, Bash Shell, SED, and AWK. He has also worked with clients to pull personnel information from legacy mainframe systems. He has also designed and implemented test code in SAS, STATA and Matlab in order to test the capabilities of a new network server and to gauge performance relative to the current server.

U.S. SECURITIES AND EXCHANGE COMMISSION

Selected casework

- Insider Trading: calculate ill-gotten gains from trades made with material non-public information; demonstrate unusual trading activity in context of historical trading behavior
- IPO market analysis: write code to replicate the workings of an IPO matching engine for a major stock exchange; examine the dynamics of the IPO using millions of orders and cancellations and test the predicted outcome against actual outcomes to identify the impact of the exclusion of a set of orders
- MIDAS interface: developed code to interface with MIDAS, a data system providing fine detailed level of equities and options trading across the various exchanges.
- Financial Misreporting
 - Apply event study methodology to measure stock price reaction and stock price inflation related to improper financial reporting
 - Calculate ill-gotten gains for “in the know” executives who exercised stock options during period of stock price inflation
 - Calculate benefits to corporation arising from transactions conducted, such as stock issuance, borrowing, acquisitions, options granting and exercise
 - Calculate harm shareholders who bought and sold stock during period of stock price inflation
- Investment Adviser Abuses
 - Detect patterns of preferential allocation (“cherry-picking”) of winning trades to favored accounts, design statistical tests to demonstrate the improbability of patterns of returns in favored and un-favored accounts, calculate
 - Identify patterns of excessive mark-ups, churning and switching trades, and non-suitable trades
 - Calculate harm to investors and adviser’s ill-gotten gains

SELECTED CONSULTING EXPERIENCE

In the private sector, Mr. Graham conducted large scale data analysis, econometric modeling, statistical sampling, and business forecasting. He also designed and implemented software tools to support business decision-making. These projects spanned many industries, including telecommunications, transportation, banking, securities and finance, and retail sales.

- Mr. Graham designed and built a database and GUI front-end to allow users to access and create various charts from a company's financial information database in order to visualize the data along various dimensions selected by the user.
- He designed a software tool to determine profit-maximizing prices for one of the largest beer brewers in Mexico using kNitro software. He improved the optimization speed and results compared to the previous tool and he automated data input feeds and added new capabilities to the output analyses.
- Mr. Graham designed and built a software tool for a major transportation client to determining optimal pricing on various city-to-city routes.
- He led a team of economists and programmers on a large scale, multi-year project for a federal agency in the resolution of troubled financial institutions. His team estimated the uninsured deposits and other measures of financial strength of the institutions. He led the effort to migrate the suite of data analyses from MS Access to MS SQL, implement other process improvements and quality controls. He also designed and managed the development and implementation of a database and GUI to track and report upon the status of many ongoing bank examinations.
- Mr. Graham managed the regulatory reporting effort for a major telecommunications client for three years. He developed a software system to perform complex statistical and financial calculations on millions of telephone and produce monthly reports on hundreds of performance metrics for the client and state and federal regulators.

Appendix 2: Facts and Data Considered

Publications

Asquith, Paul, M. Mikhail, and A. Au, “Information Content of Equity Analyst Reports,” *Journal of Financial Economics*, Volume 75, Issue 2, February 2005, Pages 245–282.

CFA Institute, *Global Investment Performance Standards Handbook*: 3rd edition, 2012.

Fama, Eugene, and K. French, “The cross-section of expected stock returns,” *Journal of Finance* 47, 1992, 427-465.

Fairfield, P., S. Ramnath, T. Lombardi Yohn, “Do Industry-Level Analyses Improve Forecasts of Financial Performance?” *Journal of Accounting Research*, Vol. 47 No. 1 (March 2009).

Graham, J., C. Harvey and S. Rajgopal, “The Economic Implications of Corporate Financial Reporting,” *Journal of Accounting and Economics*, Vol 40, December 2005.

Johnson, J. (1972). *Econometric Methods*. New York: McGraw-Hill.

Kaye, David H. and Freedman, David A., “Reference Guide on Statistics,” in *Reference Manual on Scientific Evidence* (Washington, DC: Federal Judicial Center, 3rd ed., 2011).

Rees, L., and K. Sivaramakrishnan, “The Effect of Meeting or Beating Revenue Forecasts on the Association between Quarterly Returns and Earnings Forecast Errors,” *Contemporary Accounting Research*, Vol. 24 No. 1 (Spring 2007).

Rubinfeld, Daniel, “Reference Guide on Multiple Regression,” in *Reference Manual on Scientific Evidence* (Washington, DC: Federal Judicial Center, 3rd ed., 2011).

Bates-Identified Documents

SECP-COF-00009840.pdf	SECP-COF-00012548.pdf	SECP-COF-00013567.pdf
SECP-COF-00009907.pdf	SECP-COF-00012616.pdf	SECP-COF-00013635.pdf
SECP-COF-00009974.pdf	SECP-COF-00012684.pdf	SECP-COF-00013703.pdf
SECP-COF-00010041.pdf	SECP-COF-00012752.pdf	SECP-COF-00013771.pdf
SECP-COF-00010108.pdf	SECP-COF-00012819.pdf	SECP-COF-00013839.pdf
SECP-COF-00010175.pdf	SECP-COF-00012887.pdf	SECP-COF-00014957.pdf
SECP-COF-00010242.pdf	SECP-COF-00012955.pdf	SECP-COF-00013907.pdf
SECP-COF-00011917.pdf	SECP-COF-00013023.pdf	SECP-COF-00013977.pdf
SECP-COF-00012051.pdf	SECP-COF-00013091.pdf	SECP-COF-00014047.pdf
SECP-COF-00012185.pdf	SECP-COF-00013159.pdf	SECP-COF-00014117.pdf
SECP-COF-00012253.pdf	SECP-COF-00013227.pdf	SECP-COF-00014187.pdf
SECP-COF-00012276.pdf	SECP-COF-00013295.pdf	SECP-COF-00014257.pdf
SECP-COF-00012344.pdf	SECP-COF-00013363.pdf	SECP-COF-00014327.pdf
SECP-COF-00012412.pdf	SECP-COF-00013431.pdf	SECP-COF-00014397.pdf
SECP-COF-00012480.pdf	SECP-COF-00013499.pdf	SECP-COF-00014467.pdf

SECP-COF-00014537.pdf	SECP-COF-00016229.pdf	SECP-COF-00017933.pdf
SECP-COF-00014607.pdf	SECP-COF-00016300.pdf	SECP-COF-00018004.pdf
SECP-COF-00014677.pdf	SECP-COF-00016371.pdf	SECP-COF-00018075.pdf
SECP-COF-00014747.pdf	SECP-COF-00016442.pdf	SECP-COF-00018146.pdf
SECP-COF-00014817.pdf	SECP-COF-00016513.pdf	SECP-COF-00018217.pdf
SECP-COF-00014887.pdf	SECP-COF-00016584.pdf	SECP-COF-00018288.pdf
SECP-COF-00015027.pdf	SECP-COF-00016655.pdf	SECP-COF-00018359.pdf
SECP-COF-00015097.pdf	SECP-COF-00016726.pdf	SECP-COF-00018430.pdf
SECP-COF-00015167.pdf	SECP-COF-00016797.pdf	SECP-COF-00018501.pdf
SECP-COF-00015237.pdf	SECP-COF-00016868.pdf	SECP-COF-00018572.pdf
SECP-COF-00015288.pdf	SECP-COF-00016939.pdf	SECP-COF-00018643.pdf
SECP-COF-00015306.pdf	SECP-COF-00017010.pdf	SECP-COF-00018714.pdf
SECP-COF-00015377.pdf	SECP-COF-00017081.pdf	SECP-COF-00018785.pdf
SECP-COF-00015448.pdf	SECP-COF-00017152.pdf	SECP-COF-00018856.pdf
SECP-COF-00015519.pdf	SECP-COF-00017223.pdf	SECP-COF-00018927.pdf
SECP-COF-00015590.pdf	SECP-COF-00017294.pdf	SECP-COF-00018998.pdf
SECP-COF-00015661.pdf	SECP-COF-00017365.pdf	SECP-COF-00019069.pdf
SECP-COF-00015732.pdf	SECP-COF-00017436.pdf	SECP-COF-00019140.pdf
SECP-COF-00015803.pdf	SECP-COF-00017507.pdf	SECP-COF-00019262.pdf
SECP-COF-00015874.pdf	SECP-COF-00017578.pdf	SECP-COF-00019516.pdf
SECP-COF-00015945.pdf	SECP-COF-00017649.pdf	SECP-COF-00019539.pdf
SECP-COF-00016016.pdf	SECP-COF-00017720.pdf	SECP-COF-00019557.pdf
SECP-COF-00016087.pdf	SECP-COF-00017791.pdf	SECP-COF-00019596.pdf
SECP-COF-00016158.pdf	SECP-COF-00017862.pdf	

Court Documents, Expert Reports, and Other Case Materials

Complaint, Securities and Exchange Commission v. Bonan Huang and Nan Huang, Case No. 2:15-cv-00269-MAK (E.D. Pa.)

Plaintiff's First Set of Interrogatories Directed to Bonan Huang

Plaintiff's First Set of Documents, Electronically Stored Information, and Tangible Things Requested from Bonan Huang

Plaintiff's First Set of Documents, Electronically Stored Information, and Tangible Things Requested from Nan Huang

Plaintiff's First Set of Interrogatories Directed to Nan Huang

Plaintiff's First Set of Requests for Admission Directed to Bonan Huang

Plaintiff's First Set of Requests for Admission Directed to Nan Huang

Plaintiff's Second Set of Interrogatories Directed to Bonan Huang

Plaintiff's Second Set of Interrogatories Directed to Nan Huang

Plaintiff's Second Set of Documents, Electronically Stored Information, and Tangible Things Requested from Bonan Huang

Plaintiff's Second Set of Documents, Electronically Stored Information, and Tangible Things Requested from Nan Huang

Plaintiff's Third Set of Interrogatories Directed to Bonan Huang

Plaintiff's Third Set of Interrogatories Directed to Nan Huang

Plaintiff's Third Set of Documents, Electronically Stored Information, and Tangible Things Requested from Bonan Huang

Plaintiff's Third Set of Documents, Electronically Stored Information, and Tangible Things Requested from Nan Huang

Bonan Huang's Responses and Objections to Plaintiff's First Set of Documents, Electronically Stored Information, and Tangible Things Requested from Bonan Huang

Defendant's Responses and Objections to Plaintiff's First Set of Interrogatories Directed to Bonan Huang

Nan Huang's Responses and Objections to Plaintiff's First Set of Documents, Electronically Stored Information, and Tangible Things Requested from Nan Huang

Defendant's Responses and Objections to Plaintiff's First Set of Interrogatories Directed to Nan Huang

Defendant Bonan Huang's Answers to Plaintiff's Second Set of Interrogatories

Defendant Bonan Huang's Answers to Plaintiff's Third Set of Interrogatories

Defendant Bonan Huang's Responses to Plaintiff's Third Set of Requests For Documents, Electronically Stored Information, and Tangible Things

Defendant Bonan Huang's Responses to Plaintiff's Second Set of Requests for Documents, Electronically Stored Information, and Tangible Things

Defendant Nan Huang's Answers to Plaintiff's Second Set of Interrogatories

Defendant Bonan Huang's Answers to Plaintiff's Third Set of Interrogatories

Defendant Nan Huang's Responses to Plaintiff's Second Set of Requests for Documents, Electronically Stored Information, and Tangible Things

Defendant Nan Huang's Responses to Plaintiff's Third Set of Requests for Documents, Electronically Stored Information, and Tangible Things

Defendant Bonan Huang's Answers to Plaintiff's First Set of Requests for Admission

Defendant Nan Huang's Answers to Plaintiff's First Set of Requests for Admission

Defendant Bonan Huang's Supplemental Answers to Plaintiff's Second Set of Interrogatories

Defendant Nan Huang's Supplemental Answers to Plaintiff's Second Set of Interrogatories

SEC Filings

Wal-Mart 8-K, filed Aug 15, 2013.

Brokerage Statements

Nan Huang brokerage statements from the following accounts: OptionsHouse (5PD-45586, 5PD-64034, 5PD-64046), Interactive Brokers (U1330854), COR Clearing /Just2Trade (68265967), E*Trade (67956338), Zecco Trading (4ZW83710) and MB Trading (2FC-12888).

Bonan Huang brokerage statements from the following accounts: OptionsHouse (5PD-69674, 5PD-91874, 4ZE-89435), Scottrade (68386941), TradeStation (17402409, 17410233), and E*Trade (68427490).

Publicly-Available Data Sources

Hedge fund returns from Lipper TASS Hedge Fund Database (04/01/2015).

Analyst forecasts and company actual reported financial data from Thomson Reuters I/B/E/S.

Company financial data from Standard and Poor's Compustat.

Electronic Files from Dr. Matthew Cain

- List of securities and announcement dates that the Defendants traded near
- File with summary of Defendants' trading profits

Electronic Files from Defendants' Hard Drives

"DONE" files:

aap.xls	aapl.xls	acom.xls	aeo.xls	anf.xls	angi.xls	ann.xls	aro.xls	asna.xls	azo.xls	bbby.xls	bby.xls
bebe.xls	bgfv.xls	big.xls	bke.xls	bks.xls	bont.xls	bwld.xls	bws.xls	cab.xls	car.xls	casy.xls	cato.xls
cbrl.xls	cec.xls	chs.xls	chuy.xls	cmg.xls	cmrg.xls	coh.xls	colm 2.xls	colm.xls	crbl.xls	cri 2.xls	cri.xls
crm.xls	cstr.xls	ctct.xls	ctrn.xls	dds.xls	dest.xls	dfrg.xls	dg.xls	dks.xls	dltr.xls	dpz.xls	dri.xls
dsw.xls	dtg.xls	eth 2.xls	eth.xls	expe 2.xls	expe.xls	expr.xls	fb.xls	fdo.xls	finl.xls	five.xls	fl.xls
fnp.xls	fosl 2.xls	fosl.xls	fran.xls	gco.xls	ges 2.xls	ges.xls	gman.xls	gme.xls	gnc.xls	grpn.xls	hd.xls
hhg.xls	hibb.xls	hrb.xls	hsni.xls	jack 2.xls	jack.xls	jcp.xls	jmba 2.xls	jmba.xls	josb.xls	jwn.xls	kors.xls
kss.xls	ll 2.xls	ll.xls	lnkd.xls	low.xls	lulu 2.xls	lulu.xls	lzb 2.xls	lzb.xls	m.xls	med.xls	mfb.xls
mfrm.xls	mw.xls	natr.xls	nile.xls	ntri 2.xls	ntri.xls	nwy.xls	orly.xls	outr.xls	p.xls	pbi.xls	pby.xls
pcln.xls	petm 2.xls	petm.xls	pets.xls	pir.xls	plce.xls	pnra.xls	pzza.xls	rh.xls	rl 2.xls	rl.xls	rost.xls
rrgb.xls	rt.xls	rue.xls	ruth.xls	sbux.xls	scss.xls	scvl.xls	seas 2.xls	seas.xls	sfly.xls	shos.xls	shw.xls
sig.xls	six.xls	sks.xls	skx 2.xls	skx.xls	smrt.xls	spls.xls	ssi.xls	stmp.xls	swy.xls	tea.xls	tfm.xls
tgt.xls	thi.xls	tif.xls	tjx.xls	tlvs.xls	tmp.xls	trla.xls	trlg.xls	trxn_dt.xls	tsco.xls	tumi.xls	txrh 2.xls
txrh.xls	ua.xls	ulta.xls	urbn2.xls	vpri.xls	vra.xls	vsi.xls	vz.xls	wag.xls	wmar.xls	wmt.xls	wsm.xls
wtsl.xls	yelp.xls	z.xls	zumz.xls								

REVEst((Autosaved-304182402364710960)).xls

REVEst.xls

REVEst_bkup2.xls

REVEst_tst1.xls

REVEst_tst2.xls

SECP-COF-00019653.txt

txn_mon2.btq

q3_2012_bkup.xls

85 files in kwo874 (extracted from e-mails):

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_P_I01_00000819.xls	_P_I01_00000820.xls	_P_I01_00000827.xls	_P_I01_00000840.xls	_P_I01_00000843.xls
_P_I01_00000845.xls	_P_I01_00000850.xls	_P_I01_00000854.xls	_P_I01_00000856.xls	_P_I01_00000858.xls
_P_I01_00000860.xls	_P_I01_00000862.xls	_P_I01_00000865.xls	_P_I01_00000869.xls	_P_I01_00000871.xls
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_P_I01_00000899.xls	_P_I01_00000907.xls	_P_I01_00000919.xls	_P_I01_00000926.xls	_P_I01_00000928.xls
_P_I01_00000936.xls	_P_I01_00000942.xls	_P_I01_00000943.xls	_P_I01_00000945.xls	_P_I01_00000946.xls
_P_I01_00000953.xls	_P_I01_00000962.xls	_P_I01_00000970.xls	_P_I01_00000972.xls	_P_I01_00002884.xls
_P_I01_00002885.xls	_P_I01_00002886.xls	_P_I01_00002892.xls	_P_I01_00002893.xls	_P_I01_00002895.xls
_P_I01_00002900.xls	_P_I01_00002902.xls	_P_I01_00002905.xls	_P_I01_00002908.xls	_P_I01_00002909.xls
_P_I01_00002912.xls	_P_I01_00002915.xls	_P_I01_02792942.xls	_P_I01_02792948.xls	_P_I01_02792952.xls
_P_I01_02793001.xls	_P_I01_02793004.xls	_P_I01_02793008.xls	_P_I01_02793013.xls	_P_I01_02793014.xls
_P_I01_02793016.xls	_P_I01_02793018.xls	_P_I01_02793019.xls	_P_I01_02793028.xls	_P_I01_02793052.xls
_P_I01_02793055.xls	_P_I01_02793063.xls	_P_I01_02793067.xls	_P_I01_02793069.xls	_P_I01_02793077.xls
_P_I01_02793079.xls	_P_I01_02793082.xls	_P_I01_02793084.xls	_P_I01_02793086.xls	_P_I01_02793096.xls
_P_I01_02793100.xls	_P_I01_02793103.xls	_P_I01_02793104.xls	_P_I01_02793107.xls	_P_I01_02793109.xls
_P_I01_02793113.xls	_P_I01_02793117.xls	_P_I01_02793120.xls	_P_I01_02793133.xls	_P_I01_02793137.xls

Microsoft Access databases:

MUSAVA	SOU2
OldHistory 2.mdb	OldHistory 2.mdb
OldHistory.mdb	OldHistory 3.mdb
queryman 2.mdb	OldHistory.mdb
queryman.mdb	queryman.mdb
SQLHistory 2.mdb	SQLHistory 2.mdb
SQLHistory 3.mdb	SQLHistory4.mdb
SQLHistory.mdb	SQLHistoy.mdb

Exhibit A: Examples of SQL Programs**SQL Program Submitted by 'SOU2' (Nan Huang) on 5/12/2012**
from Seq 48096 of SQLHistory.mdb

```

SEL
SUBSTR(trxn_post_dt, 1, 7) AS trxn_mth,
SUM(CASE WHEN debit_cr_cd = 'D' THEN trxn_amt
      WHEN debit_cr_cd = 'C' THEN trxn_amt *(-1) END) AS trxn_amt,
COUNT(*) AS trxn_cnt
FROM pcdw.t2_postd_trxn a
WHERE tsys_tcat_class_cd IN ('PR')
A
ND trxn_post_dt BETWEEN '2009-01-01' AND CURRENT_DATE
AND mrch_nm LIKE ANY ('%walmart%', '%wal-mart%', '%wal mart%', '%samsclub%', '%sams club%')
GROUP BY 1
ORDER BY 1
;

```

SQL Program Submitted by 'MUSAVA' (Bonan Huang) on 1/4/2014
from Seq 51083 of SQLHistory 2.mdb (abridged for space considerations)

```

delete from kwo874_svm_agent_info
where trxn_post_dt >= date - 5;
insert into kwo874_svm_agent_info
sel case when
(mrch_nm like any ('%home%goods%#%', '%t%j%maxx%') or (mrch_nm like '%marshalls%' and mrch_catg_cd =
5651)) then 'TJX'

when (mrch_nm like any ('%dd"%discount%', '%ross store%') and mrch_nm not in ('FORT ROSS STORE', 'RED
CROSS STORE')) then 'ROS'

when ((mrch_nm like any ('%Parisians%', '%Younkers%', '%Herberger%', '%Elder%Beer%', '%Carson%',
'%Bergner%', '%Boston Store%') and mrch_catg_cd = 5311) or (mrch_nm like '%Boston Store%' and mrch_catg_cd
= 5661) or (mrch_nm like '%bon%ton%' and mrch_catg_cd in (5311, 5965))) then 'BON'

when mrch_nm LIKE ANY('%QUILL CORPORATION%', '%staples%') AND mrch_catg_cd IN
('5111','5943','5967','5969','7399') then 'SPL'

when (mrch_nm like '%kohls%' and mrch_catg_cd = 5311) then 'KSS'

when (mrch_nm like '%the buckle %') then 'BKE'

when (mrch_nm like any ('%bath%body%works%', '%la senza%', '%victoria%secret%')) then 'LTD'

when (mrch_nm like '%stein%mart%') then 'SMR'

when (mrch_nm LIKE ANY('%macy%', '%Bloomingdale%') AND mrch_nm NOT LIKE ALL('%pharmacy%', '%BR-
NOUL%') AND mrch_catg_cd = '5311') then 'M'

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when (mrch_nm like '%target%' and mrch_catg_cd in (5399, 5310, 5411, 5311, 8043)) then 'TGT'

when (mrch_nm like any ('%banana%repu%', '%old%navy%') or (mrch_nm like '%gap%' and mrch_catg_cd in
(5999, 5964, 5651, 5641))) then 'GPS'

when (mrch_nm like '%NORDSTROM%' and mrch_catg_cd in (5311, 5814, 5965, 5969)) then 'JWN'

when (mrch_nm LIKE
ANY('%goody's%', '%goodys%', '%Steele"s%', '%stage#%', '%Peebles%', '%Palais%Royal%', '%Bealls%') AND
mrch_catg_cd IN ('5651')) then 'SSI'

when (mrch_nm like '%J%C%PENNEY%') then 'JCP'

when (mrch_nm like any ('%abercrombie%', '%hollister%') and mrch_catg_cd between 5611 and 5691 or
(mrch_nm in ('PAYPAL *HOLLISTER', 'PAYPAL *ABERCROMBIE')) or mrch_nm like '%gilly%hicks%') then 'ANF'

when (mrch_nm like '%jos%a%bank%') then 'JOS'

when ((mrch_nm like '%lululemon%') or (mrch_id like '%01190524' and mrch_catg_cd = 5691)) then 'LUL'

when (mrch_nm LIKE ('%la%z%boy%') AND mrch_catg_cd IN ('7641', '7399', '5999', '5712', '5021', '5046')) then 'LZB'

when (mrch_nm like any ('%willi%sonoma%', '%pottery%barn%', '%west elm%', '%POTTBARN%', '%pb outlet%', 'ws
outlet%', '%MARK%GRAHAM%', '%pb%teen%', '%Rejuvenation%') and mrch_catg_cd in (5719, 5969)) then 'WSM'

when (mrch_nm like any ('%willi%sonoma%', 'ws outlet%') and mrch_catg_cd in (5719, 5969)) then 'WS1'

when (mrch_nm like any ('%MOORES CLOTHING%', '%mens%wearhouse%', '%mw tux%', '%MW CLEANERS%') or
(mrch_nm like '%k & g%' and mrch_catg_cd in (5651, 5611))) then 'MW'

when (mrch_nm like '%CLDWTR CK%') then 'CWT'

when (mrch_nm like '%Barnes%Noble%') then 'BKS'

when (mrch_nm like '%NEW YORK & CO%') then 'NWK'

when (mrch_nm like '%noodles%co%' and mrch_catg_cd in (5812, 5814) and mrch_nm not like all ('%e noodle%',
'%boi%', '%cor%')) then 'NDL'

end stk, txn_dt, txn_post_dt,

SUM(CASE WHEN debit_cr_cd = 'D' THEN txn_amt
WHEN debit_cr_cd = 'C' THEN txn_amt *(-1) END) as txn_amt from pcdw.t2_postd_txn a,
pcdw.t2_acct_stat_hist_bc b
where (txn_post_dt between date - 5 and date - 1)
and stk is not null AND tsys_tcat_class_cd = 'PR' and mrch_cntry_cd like 'US%'
and a.acct_id = b.acct_id and b.acct_sfx_num = 0 and SVC_OWNr_CD NOT IN ('000086', '000087')
group by 1,2,3;

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Exhibit B: Tainted Ticker List

Ticker Symbol	Company Name	Statistically Significant Correlation
AAP	ADVANCE AUTO PARTS INC	1
AAPL	APPLE INC	1
ACOM	ANCESTRY COM INC	1
AEO	AMERICAN EAGLE OUTFITTERS INC N	1
AMZN	AMAZON COM INC	
ANF	ABERCROMBIE & FITCH CO	1
ANGI	ANGIES LIST INC	1
ANN	ANN INC	1
ARO	AEROPOSTALE INC	1
ASNA	ASCENA RETAIL GROUP INC	1
AWAY	HOMEAWAY INC	
AZO	AUTOZONE INC	1
BAGL	EINSTEIN NOAH RESTAURANT GRP INC	
BBBY	BED BATH & BEYOND INC	1
BBW	BUILD A BEAR WORKSHOP INC	
BBY	BEST BUY COMPANY INC	1
BEBE	BEBE STORES INC	
BGFV	BIG 5 SPORTING GOODS CORP	1
BIG	BIG LOTS INC	1
BJRI	BJS RESTAURANTS INC	
BKE	BUCKLE INC	1
BKS	BARNES & NOBLE INC	1
BOBE	BOB EVANS FARMS INC	
BODY	BODY CENTRAL CORP	
BONT	BON TON STORES INC	1
BSET	BASSETT FURNITURE INDUSTRIES INC	
BURL	BURLINGTON STORES INC	
BWLD	BUFFALO WILD WINGS INC	1
BWS	BROWN SHOE CO INC NEW	
CAB	CABELAS INC	1
CACH	CACHE INC	1
CAKE	CHEESECAKE FACTORY INC	
CAR	AVIS BUDGET GROUP INC	1
CASY	CASEYS GENERAL STORES INC	1
CATO	CATO CORP NEW	
CBK	CHRISTOPHER AND BANKS CORP	
CBRL	CRACKER BARREL OLD COUNTRY STOR	1
CEC	C E C ENTERTAINMENT INC	1

Ticker Symbol	Company Name	Statistically Significant Correlation
CHGG	CHEGG INC	
CHS	CHICOS FAS INC	1
CHUY	CHUYS HOLDINGS INC	
CMG	CHIPOTLE MEXICAN GRILL INC	1
CMRG	CASUAL MALE RETAIL GROUP INC	1
COH	COACH INC	1
COLM	COLUMBIA SPORTSWEAR COMPANY	1
CONN	CONNS INC	
CRCM	CARE COM INC	
CRI	CARTERS INC	1
CRM	SALESFORCE COM INC	1
CROX	CROCS INC	
CST	C S T BRANDS INC	
CSTR	COINSTAR INC	
CTCT	CONSTANT CONTACT INC	1
CTRN	CITI TRENDS INC	
CWTR	COLDWATER CREEK INC	
DDS	DILLARDS INC	1
DEST	DESTINATION MATERNITY CORP	
DFRG	DEL FRISCOS RESTAURANT GROUP IN	1
DG	DOLLAR GENERAL CORP NEW	1
DIN	DINEEQUITY INC	
DKS	DICKS SPORTING GOODS INC	1
DLTR	DOLLAR TREE INC	1
DNKN	DUNKIN BRANDS GROUP INC	1
DPZ	DOMINOS PIZZA INC	1
DRI	DARDEN RESTAURANTS INC	1
DSW	D S W INC	1
DTG	DOLLAR THRIFTY AUTOMOTIVE GRP I	1
EAT	BRINKER INTERNATIONAL INC	
EBAY	EBAY INC	
ETH	ETHAN ALLEN INTERIORS INC	
EXPE	EXPEDIA INC DE	1
EXPR	EXPRESS INC	1
FB	FACEBOOK INC	1
FDO	FAMILY DOLLAR STORES INC	
FINL	FINISH LINE INC	1
FIVE	FIVE BELOW INC	1
FL	FOOT LOCKER INC	1
FLWS	1 800 FLOWERS COM INC	
FNP	FIFTH & PACIFIC COMPANIES INC	1

Ticker Symbol	Company Name	Statistically Significant Correlation
FOSL	FOSSIL GROUP INC	1
FRAN	FRANCESCAS HOLDINGS CORP	1
FRED	FREDS INC	
FRGI	FIESTA RESTAURANT GROUP INC	
FTD	F T D COMPANIES INC	
FWM	FAIRWAY GROUP HOLDINGS CORP	
GCO	GENESCO INC	1
GES	GUESS INC	1
GMAN	GORDMANS STORES INC	1
GME	GAMESTOP CORP NEW	1
GNC	G N C HOLDINGS INC	1
GOGO	GOGO INC	1
GPS	GAP INC	
GRPN	GROUPON INC	
GT	GOODYEAR TIRE & RUBBER CO	
HD	HOME DEPOT INC	1
HGG	HHGREGG INC	
HIBB	HIBBETT SPORTS INC	1
HLF	HERBALIFE LTD	
HRB	BLOCK H & R INC	1
HSNI	H S N INC NEW	1
HTSI	HARRIS TEETER SUPERMARKETS INC	
HTZ	HERTZ GLOBAL HOLDINGS INC	
HVT	HAVERTY FURNITURE COS INC	
IRG	IGNITE RESTAURANT GROUP INC	
JACK	JACK IN THE BOX INC	
JCP	PENNEY J C CO INC	1
JMBA	JAMBA INC	
JOSB	JOS A BANK CLOTHIERS INC	1
JWN	NORDSTROM INC	1
KATE	KATE SPADE & CO	
KIRK	KIRKLANDS INC	
KKD	KRISPY KREME DOUGHNUTS INC	
KORS	MICHAEL KORS HOLDINGS LIMITED	1
KR	KROGER COMPANY	
KSS	KOHL'S CORP	1
LB	L BRANDS INC	
LL	LUMBER LIQUIDATORS HOLDINGS INC	1
LNKD	LINKEDIN CORP	
LOCO	EL POLLO LOCO HOLDINGS INC	
LOW	LOWES COMPANIES INC	1

Ticker Symbol	Company Name	Statistically Significant Correlation
LULU	LULULEMON ATHLETICA INC	1
LZB	LA Z BOY INC	1
M	MACYS INC	1
MCD	MCDONALDS CORP	
MED	MEDIFAST INC	1
MFB	MAIDENFORM BRANDS INC	
MFRM	MATTRESS FIRM HOLDING CORP	1
MIK	MICHAELS COMPANIES INC	
MUSA	MURPHY USA INC	
MW	MENS WEARHOUSE INC	1
NATR	NATURES SUNSHINE PRODUCTS INC	
NDLS	NOODLES & CO	1
NFLX	NETFLIX INC	
NGVC	NATRL GROCERS BY VIT COTTAGE INC	
NILE	BLUE NILE INC	1
NTRI	NUTRISYSTEM INC	1
NUS	NU SKIN ENTERPRISES INC	1
NWY	NEW YORK & CO INC	1
ODP	OFFICE DEPOT INC	
OMX	OFFICEMAX INC NEW	
ORLY	O REILLY AUTOMOTIVE INC NEW	1
OSTK	OVERSTOCK COM INC DEL	
OUTR	OUTERWALL INC	
P	PANDORA MEDIA INC	
PBI	PITNEY BOWES INC	1
PBPB	POTBELLY CORP	1
PBY	PEP BOYS MANNY MOE & JACK	
PCLN	PRICELINE GROUP INC	1
PETM	PETSMART INC	1
PETS	PETMED EXPRESS INC	1
PIR	PIER 1 IMPORTS INC DE	1
PLCE	CHILDRENS PLACE INC	1
PLKI	POPEYES LOUISIANA KITCHEN INC	
PNRA	PANERA BREAD CO	1
PSUN	PACIFIC SUNWEAR OF CA INC	
PTRY	PANTRY INC	
PZZA	PAPA JOHNS INTL INC	1
RAD	RITE AID CORP	
RH	RESTORATION HARDWARE HLDGS INC	1
RL	RALPH LAUREN CORP	
RLOC	REACHLOCAL INC	

Ticker Symbol	Company Name	Statistically Significant Correlation
RNDY	ROUNDYS INC	
ROST	ROSS STORES INC	1
RRGB	RED ROBIN GOURMET BURGERS INC	1
RSH	RADIOSHACK CORP	
RT	RUBY TUESDAY INC	
RUE	RUE21 INC	1
RUTH	RUTHS HOSPITALITY GROUP INC	1
SBH	SALLY BEAUTY HOLDINGS INC	
SBUX	STARBUCKS CORP	1
SCSS	SELECT COMFORT CORP	1
SCVL	SHOE CARNIVAL INC IN	1
SEAS	SEAWORLD ENTERTAINMENT INC	1
SFLY	SHUTTERFLY INC	1
SFM	SPROUTS FARMERS MARKET INC	
SHOS	SEARS HOMETOWN & OUTLET STRS IN	
SHW	SHERWIN WILLIAMS CO	1
SIG	SIGNET JEWELERS LTD	1
SIX	SIX FLAGS ENTERTAINMENT CORP	1
SKS	SAKS INC	1
SKX	SKECHERS U S A INC	1
SMRT	STEIN MART INC	1
SPLS	STAPLES INC	
SPWH	SPORTSMANS WAREHOUSE HLDGS INC	
SSI	STAGE STORES INC	1
STMP	STAMPS COM INC	1
SWY	SAFEWAY INC	1
SYX	SYSTEMAX INC	
TCS	CONTAINER STORE GROUP INC	
TEA	TEAVANA HOLDINGS INC	1
TFM	FRESH MARKET INC	1
TGT	TARGET CORP	1
THI	TIM HORTONS INC	1
TIF	TIFFANY & CO NEW	1
TJX	T J X COMPANIES INC NEW	1
TLYS	TILLYS INC	1
TPX	TEMPUR SEALY INTERNATIONAL INC	
TRLA	TRULIA INC	1
TRLG	TRUE RELIGION APPAREL INC	
TSCO	TRACTOR SUPPLY CO NEW	1
TTS	TILE SHOP HOLDINGS INC	
TUES	TUESDAY MORNING CORP	

Ticker Symbol	Company Name	Statistically Significant Correlation
TUMI	TUMI HOLDINGS INC	1
TXRH	TEXAS ROADHOUSE INC	1
UA	UNDER ARMOUR INC	1
ULTA	ULTA SALON COSMETICS & FRAG INC	1
URBN	URBAN OUTFITTERS INC	1
USNA	USANA HEALTH SCIENCES INC	
VITC	VITACOST COM INC	
VPRT	VISTAPRINT N V	1
VRA	VERA BRADLEY INC	1
VSI	VITAMIN SHOPPE INC	1
VZ	VERIZON COMMUNICATIONS INC	
WAG	WALGREEN CO	1
WFM	WHOLE FOODS MARKET INC	
WMAR	WEST MARINE INC	1
WMK	WEIS MARKETS INC	
WMT	WAL MART STORES INC	1
WSM	WILLIAMS SONOMA INC	1
WTSL	WET SEAL INC	
WTW	WEIGHT WATCHERS INTL INC NEW	
YELP	YELP INC	1
Z	ZILLOW GROUP INC	1
ZNGA	ZYNGA INC	
ZU	ZULILY INC	
ZUMZ	ZUMIEZ INC	1

Exhibit C: SQL Program from Walmart DONE File

	A	B	C	D	E	F	G	
1								
2	SEL							Aggregate transactions by month, using the transaction post date
3	SUBSTR(trxn_post_dt, 1, 7) AS txn_mth,							
4	SUM(CASE WHEN debit_cr_cd = 'D' THEN txn_amt							Aggregate credit and debit card transactions
5	WHEN debit_cr_cd = 'C' THEN txn_amt *(-1) END) AS txn_amt,							
6	COUNT(*) AS txn_cnt							
7	FROM pcdw.t2_postd_txn a							Over the period January 2001 to Current Date
8	WHERE tsys_tcat_class_cd IN ('PR')							
9	AND txn_post_dt BETWEEN '2009-01-01' AND CURRENT_DATE							
10	AND mrch_nm LIKE ANY ('%walmart%', '%wal-mart%', '%wal mart%', '%samsclub%', '%sams club%')							For Wal-Mart Stores
11	GROUP BY 1							
12	ORDER BY 1							
13	;							
14								

Sum the dollar value of transactions (txn_amt) & number of transactions (txn_cnt)

From Capital One transactions database

Aggregate transactions by month, using the transaction post date

Aggregate credit and debit card transactions

Over the period January 2001 to Current Date

For Wal-Mart Stores

EXHIBIT D
TO BE FILED UNDER SEAL

Exhibit E: Charts for 20 DONE Files

